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AMIAD
Agence ministérielle pour l'intelligence artificielle de défense

Open-source off-road autonomous navigation stack using LiDAR or monocular vision

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3DPNV 01/09/26

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LARIAD, an AMIAD-ENSTA joint laboratory

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LARIAD – joint AMIAD-ENSTA laboratory

- Joint laboratory led by David Filliat (AMIAD) and Alexandre Chapoutot (ENSTA)

- Objectives:
  - Pool human and material resources
  - Improve our visibility
  - Becoming a reference academic center on AI for defense robotics

- Research areas:
  - Off-road navigation
  - Swarm Area Exploration
  - Human-robot interaction
  - Trusted AI

Offroad navigation in difficult scenarios

- Outdoor: high-grass, ferns, negative obstacles, mud, …
- **Using LiDAR or moncular vision**

Experimental area example

Barakuda robot from ENSTA

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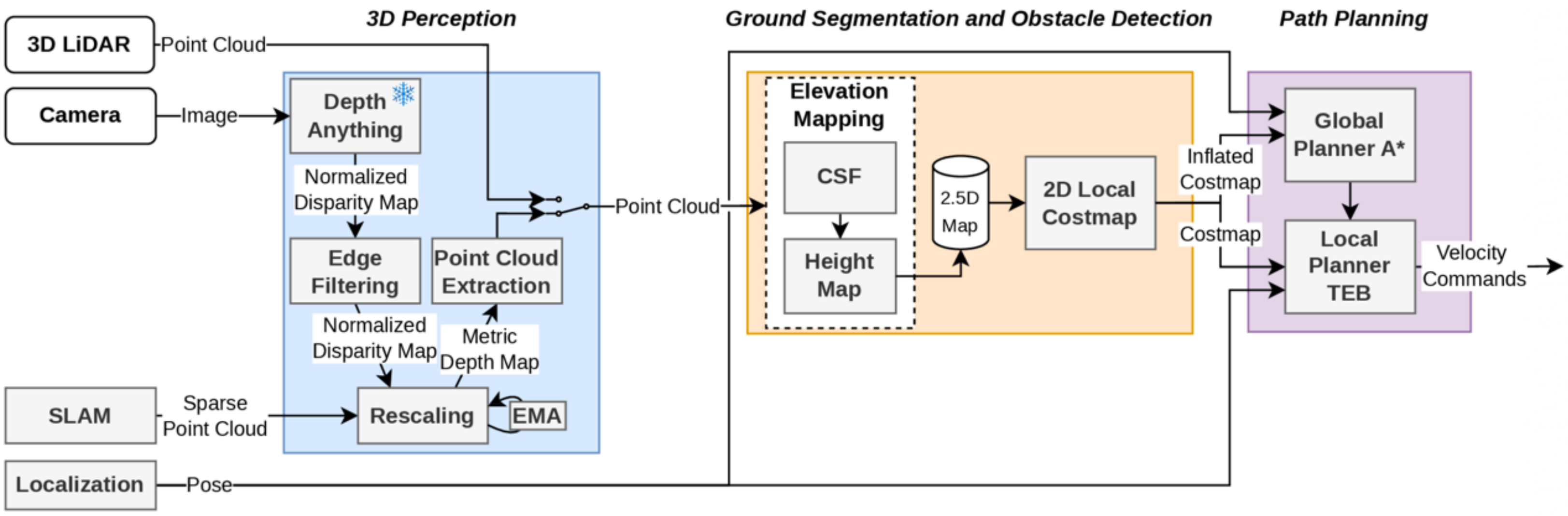
Navigation stack

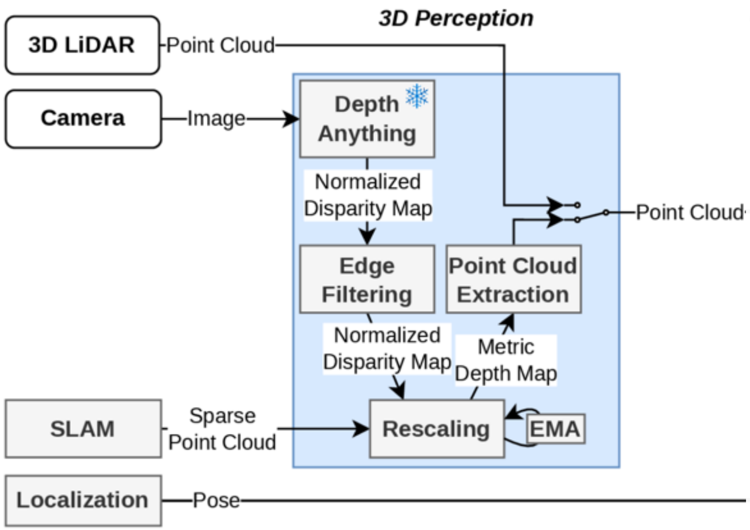
(Picard et al., 2026)

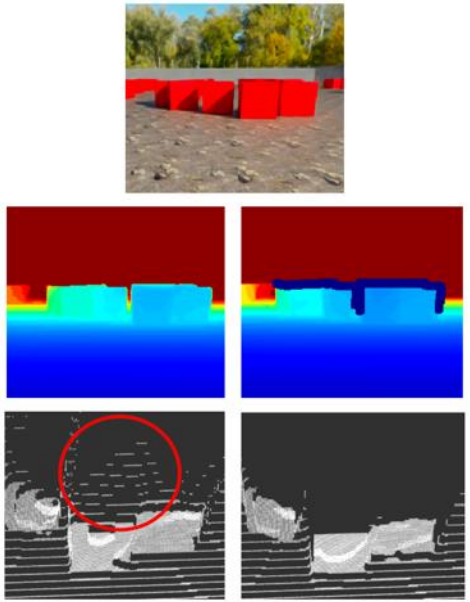
- Common pipeline with LiDAR or monocular vision point clouds
- Based on several existing open source models
- Integrated and tested on several robots and simulations



Point cloud from monocular vision

(Marsal et al., 2025)





- Disparity map contour filtering with Sobel filter
- Scale parameter estimated from sparce metric points from VIO
- Temporal filtering for smoothing

$$\tilde{\mathbf{s}}_t = \alpha\tilde{\mathbf{s}}_{t-1} + (1-\alpha)\hat{\mathbf{s}}_t$$

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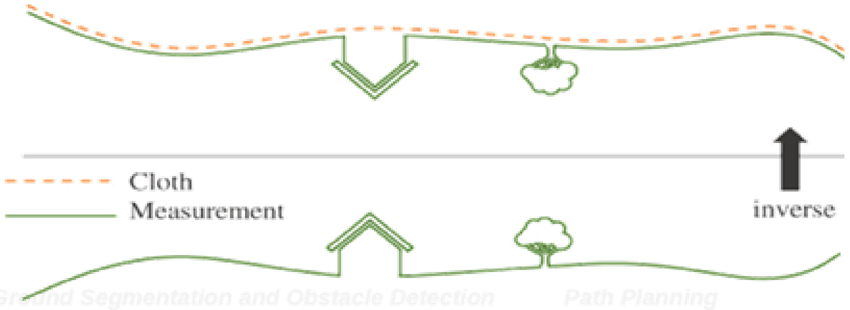
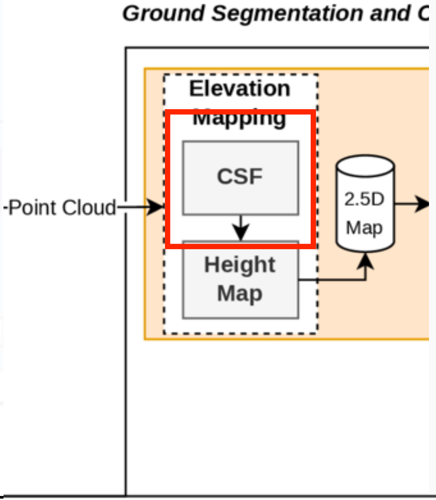
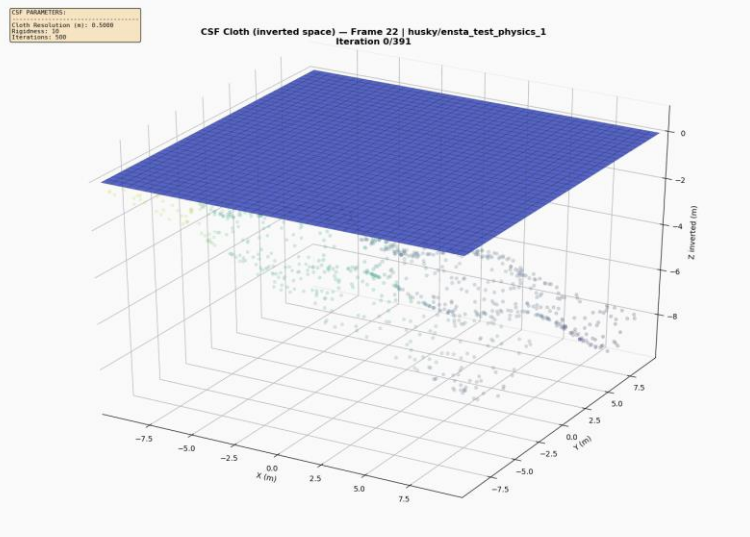
Non-flat ground segmentation

Cloth Simulation Filter (Zhang et al., 2016)

1. Invert the point cloud
2. Initialize the « cloth » above the surface
3. Find the minimum Z-value of the points in each cell of the cloth
4. Simulate the cloth fall under various constraints (gravity, stiffness, iterations, etc.)
5. Classify points as ground or non-ground based on distance to cloth
6. Compute height of each point wrt the ground



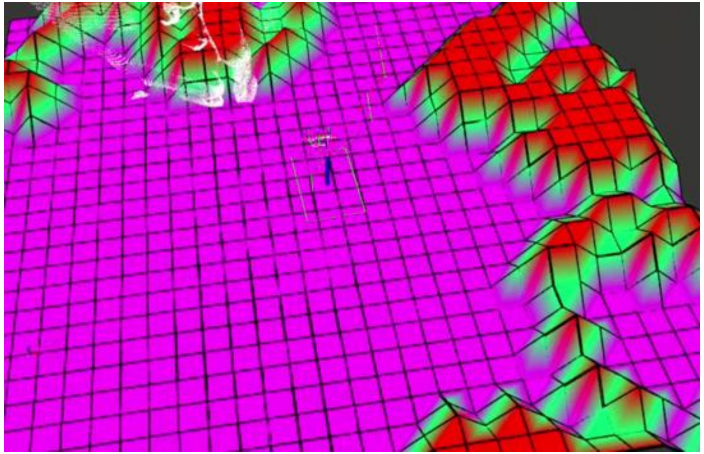


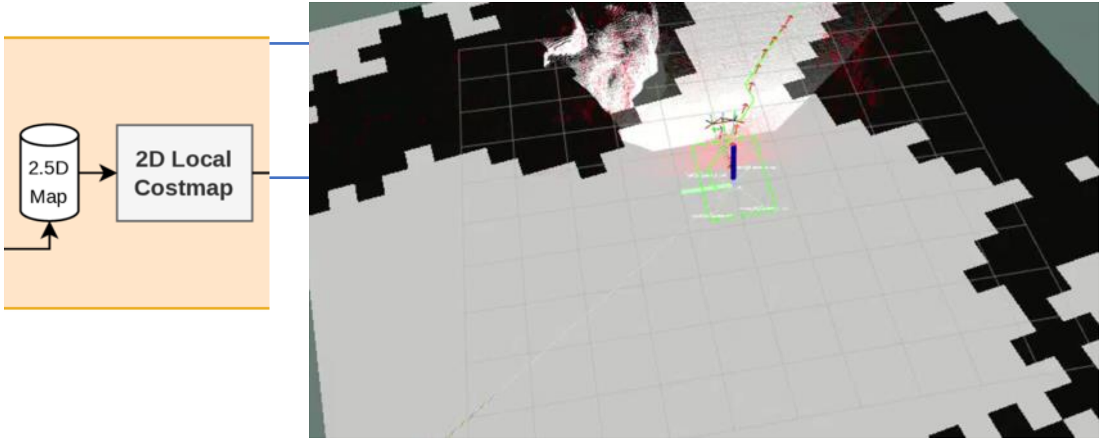


Obstacle detection

(Miki et al., 2022)

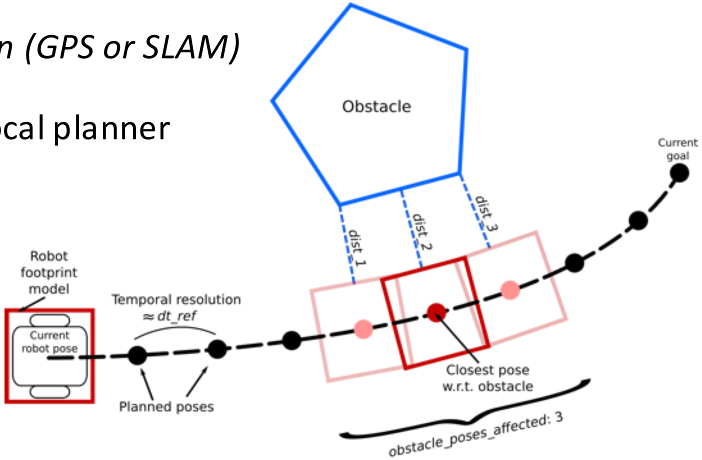
- *Elevation mapping cupy* to store height maps and compute various characteristics
- *grid_map_costmap_2d* to provide local cost for planning

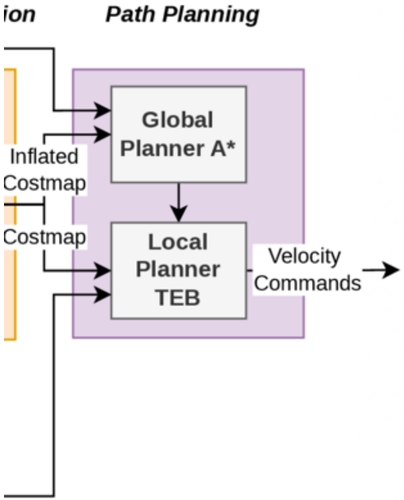




Local path planning

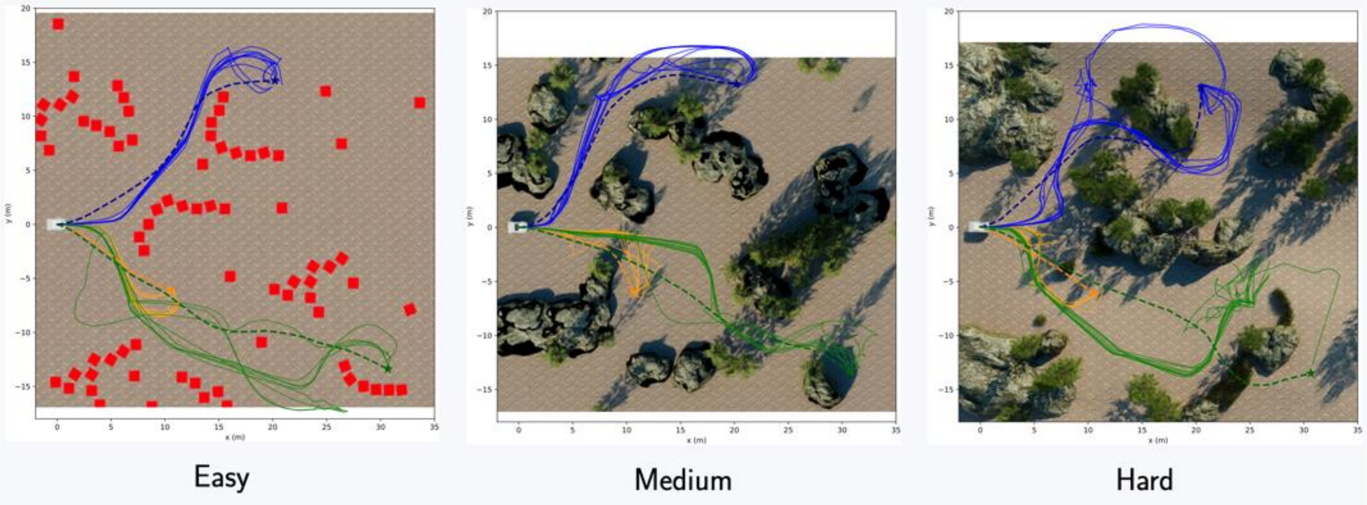
- Based on the *Move Base Flex* architecture
- *Assume existing localization (GPS or SLAM)*
- TEB (*Timed Elastic Band*) local planner





- A* global planning
  - No global map at the moment
  - Unknown considered free space

Extensive simulation testing (Isaac Sim)

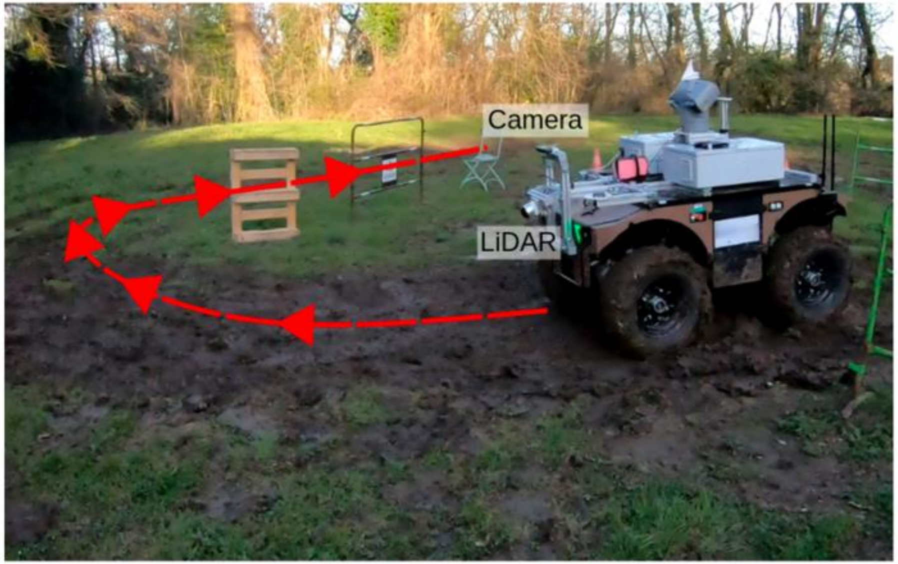


LiDAR and monocular navigation performances are similar

More difficult for monocular in front of high grass (Hard)

Implemented and tested on Barakuda robots

- Sensors:
  - Ouster Dome LiDAR 128
  - ZED2i Camera
  - SBG IMU
  - GNSS
- Jetson ORIN 64GB with ROS1 Noetic middleware
- GNSS et LIO fused by EKF (robot_localization) for localization
- Currently ported to smaller robots with ONERA



Real results

Easy Medium Hard

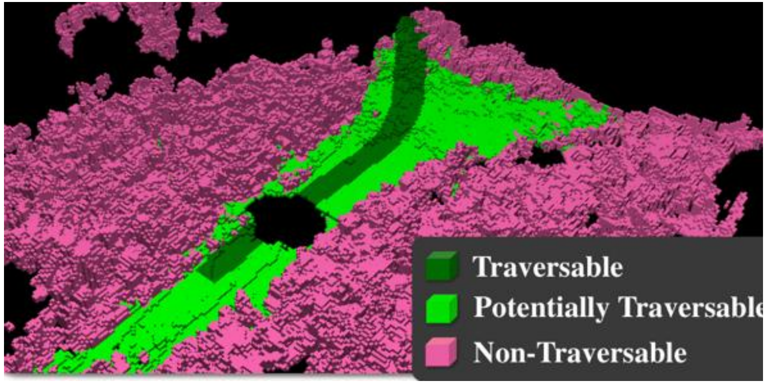
	Easy			Medium			Hard			Average		
	SR	SPL	DR	SR	SPL	DR	SR	SPL	DR	SR	SPL	DR
LiDAR	**1.0**	**0.73**	**1.0**	**1.0**	**0.68**	**1.0**	**1.0**	**0.67**	**1.0**	**1.0**	**0.69**	**1.0**
Mono-VINS	**1.0**	0.51	**1.0**	**1.0**	0.63	**1.0**	**1.0**	0.63	**1.0**	**1.0**	0.59	**1.0**

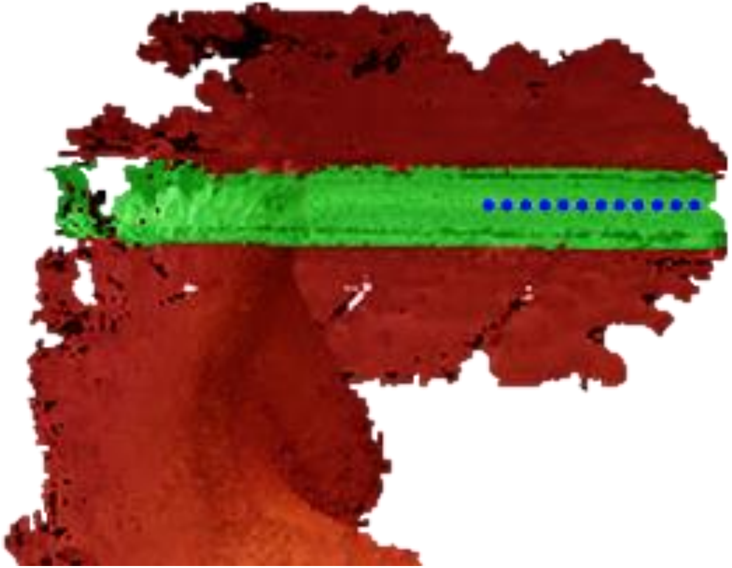
SR : Success rate
SPL : success weighted by path length
DR : Distance Ratio (for failed paths)

Smaller SPL pour Mono-VINS (0.59 vs 0.69) because of longer computation times (delays)

A better (learned) traversability model

- Need for data
  - Large volume required for generalization
  - Existing semantic labels (**road, path, grass, vegetation, vehicle, tree**) are insufficient
  - Large-scale labeling is difficult/costly
- Self-annotated (self-supervised) data
  - The robot's future path indicates traversable areas
  - But provides no information about the rest
  - One class learning / Positive Unlabeled learning

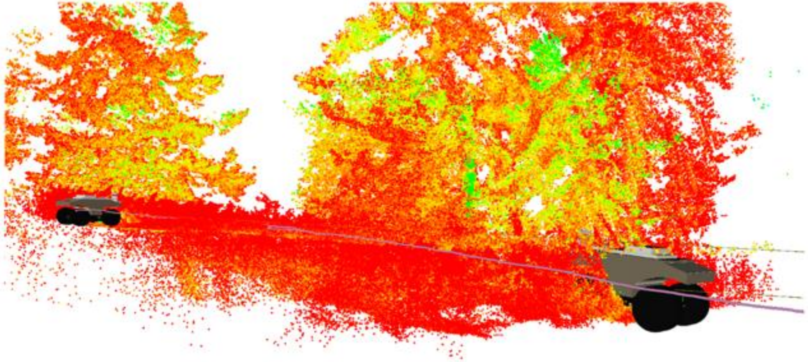




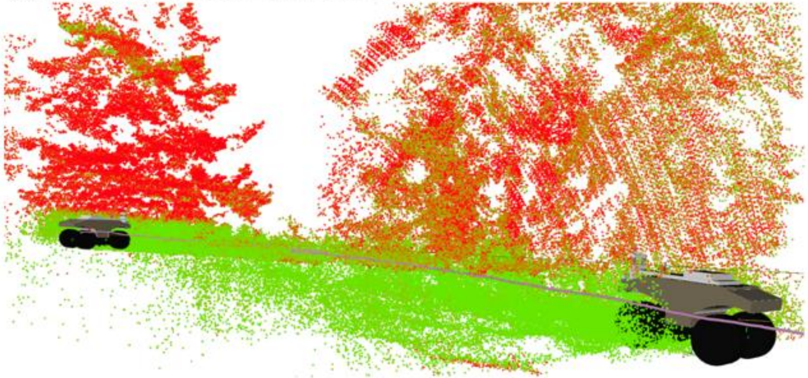
Ongoing work

- Several approach tested
  - Discriminative loss + Weighting unlabeled example as negatives according to similarity with positive
  - Learning representation using contrastive loss with probabilistic choice of negatives
  - One class learning to learn positive representation in a sphere

(a) A composite image showing the Barakuda UGV during data collection via manual teleoperation.



(b) A point cloud visualization from the dataset, colored by LiDAR reflectivity.



(c) Example traversability prediction from the `MinkUNet (EmbVAE-16)` model on the same scene. Traversable ground is green, while obstacles are red.

Outlook

- Foundation model-based monocular depth estimation is a viable alternative.
- Reproducible results! Code and simulation are open source.
- Good baseline to test ML modules wrt classical baselines (traversability, end-to-end, …)
- Useful to produce training data
- Open to the community to ensure long-term maintenance

- Future work: Handling negative obstacles + traversing tall grass.

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ROS2 Jazzy version available soon !